SAR Image Processing Using Artificial Intelligence Planning

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Abstract—In recent times, improvements in imaging technology have made available an incredible array of information in image format. While powerful and sophisticated image processing software tools are available to prepare and analyze the data, these tools are complex and cumbersome, requiring significant expertise to properly operate. Thus, in order to extract (e.g., mine or analyze) useful information from the data, a user (in our case a scientist) often must possess both significant science and image processing expertise.

This paper describes the use of Artificial Intelligence (AI) planning techniques to represent scientific, image processing, and software tool knowledge to automate elements of science data preparation and analysis of *synthetic aperture radar* (SAR) imagery for planetary geology. In particular, we describe the Automated SAR Image Processing system (ASIP) which is currently in use by the Department of Geology at Arizona State University (ASU) supporting aeolian science analysis of synthetic aperture radar images. ASIP reduces the number of manual inputs in science product generation by 10-fold, decreases the CPU time to produce images by 30%, and allows scientists to directly produce certain science products.

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1. INTRODUCTION

Recent breakthroughs in imaging technology have led to an explosion of available data in image format. However, these advances in imaging technology have brought with them a commensurate increase in the complexity of image processing and analysis technology. When analyzing newly available image data to discover patterns or to confirm scientific theories, a complex set of operations is often required. First, before the data can be used it must often be reformatted, cleaned, and many correction steps must be applied. Then, in order to perform the actual data analysis, the user must manage all of the analysis software packages and their requirements on format, required information, etc.

Furthermore, this data analysis process is not a one-shot process. Typically a scientist will set up some sort of analysis, study the results, and then use the results of this analysis to modify the analysis to improve it. This analysis and refinement cycle may occur many times - thus any reduction in the scientist effort or cycle time can dramatically improve scientist productivity. Consider the goal of studying the soil sediment transport (wind erosion patterns). In order to do this the scientist uses a z0map (described later) to analyze the surface wind velocities using SAR data. In order to generate the z0map the scientist must go through a number of processes:

(1) data acquisition: getting the data from a proprietary tape format using the CEOS reader software package
(2) data conversion: the data must be decompressed using yet another software package
(3) pre-processing: header and label files must be added to the date files
(4) processing: using the z0map software package a z0 map image is created and
(5) post processing: depending on the desired data format the z0 map image files may need to be converted to VICAR format (yet another proprietary format).

Unfortunately, this data preparation and analysis process is both knowledge and labor intensive.

To correctly produce this science product for analysis, the scientist must have knowledge of a wide range of sources including:

(1) the particular science discipline of interest (e.g., atmospheric science, planetary geology),
(2) image processing and the image processing libraries available,
(3) where and how the images and associated information are stored (e.g., calibration files), and
(4) the overall image processing environment to know how to link together libraries and pass information from one program to another.

It takes many years of training and experience to acquire the knowledge necessary to perform these analyses, putting these experts in high demand. One factor that exacerbates this shortage of experts, is the extreme breadth of knowledge required. Many users might be knowledgeable in one or more of the above areas, but not in all of the areas. In addition, the status quo requires that users possess considerable knowledge about software infrastructure. Users must know how to specify input parameters (format, type, and options) for each software package that they are using and must often expend considerable effort in translating information from one package to another.

Using automated planning technology to represent and automate many of these data analysis functions [9](page 50) [6] enables novice users to utilize the software libraries to prepare and analyze data. It also allows users who may be expert in some areas but less knowledgeable in others to use the software tools.

The remainder of this article is organized as follows. First, we provide a brief overview of the key elements of AI planning. We then describe the ASIP system, which automates elements of image processing science data analysis of synthetic aperture radar (SAR) images.

2. Artificial Intelligence Planning Techniques

We have applied and extended techniques from Artificial Intelligence planning to address the knowledge-based software reconfiguration problem [5] in general, and science data analysis in particular. In order to describe this work, we first provide a brief overview of the key concepts from planning technology[1].

Planning technology relies on an encoding of possible actions in the domain. In this encoding, one specifies for each action in the domain: *preconditions*, *post-conditions*, and *sub-activities*. Preconditions are requirements that must be met before the action can be taken. These may be pieces of information, which are required to correctly apply a software package (such as the image format, availability of calibration data, etc.) Post-conditions are things that are made true by the execution of the actions, such as the fact that the data has been photometrically corrected (corrected for the relative location of the lighting source) or that 3-dimensional topography information has been extracted from an image. Sub-activities are lower level activities that comprise the higher level activity. For instance, returning to our example of analyzing soil sediment transport using SAR data, the different tasks (e.g., data acquisition, data conversion, etc.) are considered subtasks of the overall product generation process. The planner begins with the process of "determining parameters". This step is driven by the type of data format or mode of the SAR equipment was in during data collection. Through this decomposition process parameters to be used in the z0map calculation are initialized. Given this encoding of actions, a planner is able to solve individual problems, where each problem is a current state and a set of goals. The planner uses its action models to synthesize a plan (a set of actions) to achieve the goals from the current state.

Planning consists of three main mechanisms: subgoaling, task decomposition, and conflict analysis. In subgoaling, a planner ensures that all of the preconditions of actions in the plan are met. This can be done by ensuring that they are true in the initial state or by adding appropriate actions to the plan. In task decomposition, the planner ensures that all high level (abstract) activities are expanded so that the lower level (sub-activities) activities are present in the plan. This ensures that the plan consists of executable activities. Conflict analysis ensures that different portions of the plan do not interfere with each other.

3. The Automated SAR Image Processing (ASIP) System

The Automated SAR Image Processing (ASIP) system automates synthetic aperture radar (SAR) image processing based on high level user request and a knowledge-base model of SAR image processing using AI automated planning techniques [10, 11]. SAR operates simultaneously in multipolarizations[2] and multifrequencies[3] to produce different images consisting of radar backscatter coefficients (s0) through different polarizations at different frequencies. ASIP enables construction of an aerodynamic roughness image/map (z0 map) from raw SAR data - thus enabling studies of Aeolian processes.

Studies of Aeolian Processes

The aerodynamic roughness length (z0) is the height above a surface at which a wind profile assumes zero velocity. z0 is an important parameter in studies of atmospheric circulation and aeolian sediment transport (in layman's terms: wind patterns, wind erosion patterns, and sand/soil drift caused by wind) [12, 13, 14]. Estimating z0 with radar is important because it enables large areas to be

[1] For further details on planning the user is referred to [20, 8]

[2] There are four combinations of polarization: HH, HV, VH, and VV, where H = Horizontal and V= Vertical.

[3] There are three frequencies used: P, L, and C bands.

mapped quickly to study aeolian processes, as opposed to the slow painstaking process of manually taking field measurements [1]. The final science product is a VICAR image called a z0 map[4] that the scientists use to study the aeolian processes. Scientists use aerodynamic roughness length to determine whether a surface in a dry land region with little or no vegetation will erode and grains will mobilize during windstorms.

z0 Map Production

As mentioned in the Introduction there are five steps involved in producing a z0-map:

(1) data acquisition
(2) data conversion
(3) pre-processing
(4) processing
(5) post-processing

The SAR data files are extracted from tape to disk using the CEOS[5] Reader software package, and an ASCII version of the CEOS imagery options file is generated. This ASCII file which is obtained from the CEOS headers associated with the SAR data file is needed by the header construction software in order to generate the header file needed for decompression of SAR data file into an image file. The common block header file consist of 6 items:

(1) data type is one of the following :
  - single pol/MLD,
  - quad pol/MLC,
  - dual pol/MLC,
  - quad pol/SLC,
  - dual pol/SLC,
  - single pol/SLC.

(2) data mode is one of the following band/polarization encodings:
  - Lquad, Cquad,
  - LHH and LVV or CHH and CVV,
  - LHH and LHV or CHH and CHV,
  - LVH and LVV or CVH and CVV,
  - LHH or CHH,
  - LVV or CVV,
  - other single pol data.

(3) input image record length
(4) number of samples[6]
(5) number of lines
(6) number of bytes per sample

The SAR data file and header file are needed by z0map software to generate a z0-map image in which a color bar scale is also included to show the height of the aerodynamic roughness length approximation as represented by color. The output z0-map image may be either in raw format or VICAR format. The z0map software converts the radar backscatter coefficients in dB into an aerodynamic roughness length approximation in meters by using the empirical model derived from field measurements of wind profiles and simultaneous AIRSAR flights. The empirical model shows strong correlation between the log value of aerodynamic roughness and the radar backscatter coefficient. The best correlation was found with L-band.

In general, the z0-map images for all of the possible polarizations and for P, L, and C bands are generated for analysis. These band-polarizations pairs consist of P-HH, P-HV, P-VV, L-HH, L-HV, L-VV, C-HH, C-HV, and C-VV.

Unfortunately, this data preparation and analysis process is both knowledge and labor intensive.

Planning to Generate Aerodynamic Roughness Maps

ASIP, an end-to-end image processing system automating data abstraction, decompression, and (radar) image processing, integrates a number of SAR and z0 image processing software packages. Using a knowledge base of SAR processing actions and a general-purpose planning engine, ASIP reasons about the parameter and sub-system constraints and requirements: extracting needed parameters from image format and header files as appropriate (freeing the user from these issues). These parameters, in conjunction with the knowledge-base of SAR processing steps (see Figure 1) and a minimal set of required user inputs (entered through a graphical user interface (GUI)), are then used to determine the processing plan. ASIP represents a number of processing constraints (e.g., only some subset of all the possible combinations of polarizations is legal, as dependent on the input data). ASIP also represents image processing knowledge about how to use polarization and frequency band information to compute parameters used for later processing of backscatter to aerodynamic roughness length conversions, thus freeing the user from having to understand these processes (see Figure 1).

```
(decomprule get_z0map_coef_l-hv
   lhs
       (initialgoals(  (get_z0map_coef l-hv)
                   )
       )
   rhs
       (newgoals(   (m0 -6.419)
                    (m1 9.957)
                    (r_chit 0)
                    (r_psit 90)
                    (r_chir 0)
                    (r_psir 0)
                    (i_polcode 2)
                    (polar l-hv)
                   )
       )
   doc [ ]
)
```

Figure 1: Sample Decomposition Rule from ASIP SAR Domain

4 z0 is pronounced "Z-naught" (as in z-axis, zero velocity)

5 Committee on Earth Observation Satellites (CEOS)

6 Number of samples collected per line (i.e. number of columns).

The design of ASIP focuses on automation to make a variety of software tools function together. In the process of accomplishing this goal, many of the interfaces of the individual tools where modified to provide automated interfaces. Through these new automated interfaces, considerable information, previously entered into each tool through an interactive shell, is passed from one tool to another. In many cases the same information must be provided to many of the tools. In some cases the information is the same but the required format may differ from one tool to another. Many of the parameters provided to the tools are interdependent on as many as five other parameters. As the parameters become more interdependent it becomes more difficult to understand the process. Through these new automated interfaces many of these parameters are passed to the planning system and the knowledge base is used by the planner to reason about the interdependencies to set the resulting parameters appropriately. Going back to the ASIP design, ASIP actually calls the planner twice. In the first call the planner determines the steps (tools) necessary to accomplish the processing task (goals); and determines how to set parameters needed in generating the header files. Once the data has been extracted and more data has been gathered, the planner is called a second time to further reason about the parameter settings needed to complete the remainder of the processing goals. The two knowledge bases combined contain 29 rules.

Figure 1 shows an example of a task decomposition rule. In the rule *get_z0map_coef_l-hv*, we see that if the *preconditions* spelled out in the *lhs* (left-hand side) are met then the parameters and coefficients of the *rhs* (right-hand side) are set for later use. Although not shown, the *lhs* of the *get_z0map_coef_l-hv* rule is satisfied by the application of other planning operators and rules.

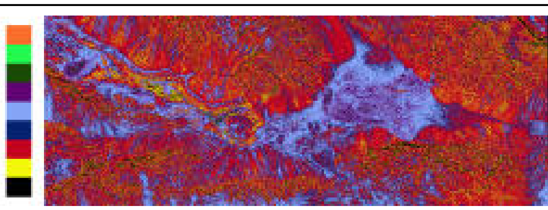

Figure 2: Aerodynamic Roughness Length Map Produced Using ASIP

Figure 2 shows an aerodynamic roughness length map of a site near Death Valley, California generated using the ASIP system (the map uses the L band (24 cm) SAR with HV polarization). This aerodynamic roughness length map or *z0-map* is the final product of the ASIP tool and image processing endeavor. Each of the color scale bands indicated signifies a different approximate aerodynamic roughness length. The scale is a logarithmic scale ranging from 1^x10^{-1} meters to 1^x10^{-5} meters. For this image the bottom of the scale represents the roughest terrain, while the top of the scale represents the smoothest terrain. This map is then used to study aeolian processes at the Death Valley site.

4. Application Use and Payoffs

Since the ASIP system was fielded in January 1997, it has proven to be very useful in the use of generating aerodynamic roughness maps with three major benefits.

(1) ASIP has enabled a 10-fold reduction in the number of manual inputs required to produce an aerodynamic roughness map.
(2) ASIP has enabled a 30% reduction in CPU processing time to produce such a map (by producing more efficient processing plans).
(3) Most significantly, ASIP has enabled scientists to process their own data. (Previously programming staff was required.)

By enabling scientists to directly manipulate the data and reducing processing overhead and turnaround, science is directly enhanced.

5. Application Development, Deployment and Maintenance

The development of the ASIP system took approximately six work months[7]. During that period, the system was developed and deployed using an iterative waterfall development cycle containing three incremental deployments. The development team consisted of one AI Planning researcher from JPL and a SAR domain expert from ASU, who later became one of the users of the system after deployment to the ASU Planetary Geology Department. The system was both developed and deployed on a Sun UNIX workstation using a combination of C, FORTRAN, and TCL/TK.

The users of the system at ASU perform the maintenance of the ASIP system. Because of the nature of the SAR domain, modifications to the knowledge base are not expected to be frequent. There are three types of information that must be maintained in the ASIP knowledge base:

(1) the values of the correlation coefficients,
(2) the relationship between the coefficients, and
(3) the relationship between the systems activities used to process the SAR data.

Because the values for the correlation coefficients are found experimentally, it is expected that this portion of the system will require the most likely modification. A need to modify these values would come through a greater understanding of the SAR data and the z0-map technique. Because of the declarative representation of the knowledge base, this is an easy modification to make. This ease of modification is a significant benefit to using a planning approach over a procedural approach.

[7] One factor contributing to the short development cycle was the use of a pre-existing general purpose planning engine.

If represented procedurally any interdependency relationship between the values or activities must be coded with in the logic of the program, generally complex nested "if" statements. This sort of approach is difficult to modify, maintain, and extend. Where as a planning representation allows for encoding these relationships in a very modular fashion, which is easy to maintain and modify. Further, this domain specific knowledge (rules) are independent from the code used to reason about them. This offers several advantages:

(1) the reasoning engine (code) can be tested and validated, independent to the changes in the domain requirements and understanding.
(2) The KB can be validated and modified independent of the engine.
(3) Different KB's can be plugged in at run time to experiment with different domain hypotheses.

There are two other benefits of the declarative representation of the knowledge-base worthy of pointing out.

(1) Because the knowledge-base is an ASCII text file loaded into ASIP at run time, modifications to processing rules do not require that the system be recompiled, as would be the case in a procedural system. This also allows for greater flexibility in tuning of parameters (coefficients) between runs.
(2) The declarative knowledge base provides a form of documentation of the image processing procedure /process.

6. Related Work

Related work can be broadly classified into the following categories: related image processing languages, related automated image processing work, and related AI planning work. In terms of related image processing languages, there are many commercial and academic image processing packages, such as IDL, Aoips, and Merlyn. Generally, these packages have only limited ability to automatically determine how to use different image processing programs or algorithms based on the problem context (e.g., other image processing goals and initial image state). These packages only support such context sensitivity for a few pre-anticipated cases.

However, there are several previous systems for automatic image processing that use a domain independent mechanism. The work at the Canadian Centre for Remote Sensing (CCRS) [4] differs from ASIP in that they use a case-based reasoning approach in which a problem is solved by searching for a previous problem and solution.

Grimm and Bunke [15] developed an expert system to assist in image processing within the SPIDER library of image processing routines. This system uses many similar approaches in that: (1) it classifies problem types similar to the fashion in which ASIP performs skeletal planning; and (2) it also decomposes larger problems into subproblems which ASIP performs in decomposition planning. This system is implemented in a combination of an expert system shell called TWAICE (which includes both rules and frames) and Prolog.

This very basic implementation language provides considerable power and flexibility but means that their overall system uses a less declarative representation than our decomposition rules and operators which have a strict semantics [8, 3].

Previous work on automating the use of the SPIDER library includes [21], which performs constraint checking, and step ordering for a set of conceptual image processing steps and generation of executable code. This work differs from ASIP in that: (1) they do not infer missing steps from step requirements; (2) they do not map from a single abstract step to a context-dependent sequence of image processing operations; and (3) they do not reason about negative interactions between subproblems. ASIP has the capability to represent and reason about all three of these cases. Other work by Jiang and Bunke [16] involves generation of image processing procedures for robotics. This system performs subgoaling to construct image-processing plans. However their algorithm does not appear to have a general way of representing and dealing with negative interactions between different subparts of the plans. In contrast, the general Artificial Intelligence Planning techniques used by ASIP use conflict resolution methods to guarantee correct handling of subproblem interactions.

Another piece of related work is the SATI system [2], which uses an interactive dialogue with the user to drive an automated programming approach to generating code to satisfy the user request. OCAPI [7], a semantically integrated automated image processing system, while being very general provides no clear way to represent the large number of logical constraints associated with the problems ASIP was designed to solve. Another image processing system [19] provides a means for representing knowledge of image analysis strategies in an expert system but does not use the more declarative AI planning representation. Perhaps the most similar planning and image processing system is COLLAGE [17]. The COLLAGE planning differs from ASIP in that COLLAGE uses solely the decomposition approach to planning.

Finally, the most closely related system to ASIP is MVP [6]. The greatest similarity being MVP and ASIP use the same AI Planning techniques to capture and reason about the knowledge of image processing. The primary differences lie in the domains and in the packaging. MVP produces VICAR procedure definition files (PDFs) for VICAR image processing [18], while ASIP performs end-to-end closed loop integration of all the tools for SAR image processing.

7. Conclusions

This paper has described knowledge-based reconfiguration of data analysis software using AI planning techniques. In particular, we have described the ASIP system, which automates production of aerodynamic roughness maps to support geological science analysis. ASIP reduces the number of manual inputs in science product generation by 10-fold, has reduced the CPU processing time by 30%, and has enabled scientists to directly produce certain science products.

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